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Planning for spare parts procurement under lack of information

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Abstract

Spare parts management continues to receive increasing interest in academic and industrial circles. Companies must place the appropriate strategies to insure a sustainable spare parts management system until the end of life (EOL). In addition to spare parts production and replacing parts under warranty, they can consider buying their used products to extract components, repairing defected items, or placing a last time buy (LTB). These options are usually considered at the products EOL. The needed data to take the decisions at the right time are usually lacking. We provide a decision support system (DSS) for spare parts procurement planning that considers these options as soon as possible in the spare part life cycle. We use recursive feature elimination (RFE) to find the most impacting features on the considered supply options availability and classify them using Hierarchical agglomerative clustering to impute missing data. Then, we calculate the optimal solution for the spare parts procurement planning until EOL. A numerical experiment is applied on a spare part from General Electric Healthcare (GEHC). We also consider a LTB in case of a programmed obsolescence. We show that considering these options can decrease the total cost by at least 9%.

Keywords: Decision support system, spare parts procurement, reuse, repair, LTB, spare parts clustering, Data imputation.

1 Introduction

Having a direct impact on the inventory and the customer serviceability, spare parts management is considered as one of the most pivotal decisions (Ghuge et al., 2022). The main operational research disciplines for supporting spare parts management are simulation, multi-criteria classification, forecasting, and optimization (Hu et al., 2018). Spare parts management relies on several pillars of these disciplines like inventory control (Do Rego and de Mesquita, 2011), optimal pricing, manufacturing strategies, warranty period (Kim and Park, 2008; Podolyakina, 2016), demand and reuse forecast (Turki et al., 2022; Boylan and Syntetos, 2010), spare parts segmentation for inventory control and for forecasting (Boylan et al., 2008), and decision support for spare parts acquisition (Hafner et al., 2021). Spare parts management is considered critical whereas their cost accounts for a large share of the products' life-cycle cost (Zhang et al., 2021) and related decisions need to be taken at the right time.

To ensure the customer satisfaction along with the profit, the company offers different maintenance services until the products end of life (EOL). Spare parts acquisition for maintenance is a challenging process for it needs to consider the spare part criticality, the suppliers lead times and reliability, the spare parts life cycle phase, the installed base (IB) size, and the spare part's consumption. The options considered for spare parts acquisition until EOL in the literature are buying new ones if they are still being manufactured, placing a final order, considering extra production runs, repairing, recycling, and spare parts harvesting from returned systems (remanufacturing) (Inderfurth and Mukherjee, 2008). At the final phase of the products life cycles, a variety of decisions can be taken so that the organizations continue to maintain the products until the EOL. The reuse of products or the spare parts composing them, remanufacturing or placing a final order in case of planned obsolescence also called a last time buy (LTB) of the spare parts can be considered (Hu et al., 2018). Inderfurth and Mukherjee (2008) and Inderfurth and Kleber (2013) proposed approaches to optimize spare parts acquisition at the post product life cycle period considering extra production runs, final orders, and remanufacturing. Xu et al. (2014) compared between recycling and remanufacturing as solutions to optimize spare parts procurement at the EOL. Tahirov et al. (2016) proposed an optimization model for parts procurement considering remanufactured and recycled spare parts from products returns and spare parts production. Additive manufacturing is also considered as an alternative to supply spare parts at the EOL (Cantini et al., 2022). The decision to acquire spare parts from these supply options can be challenging since it depends on the variability of the spare parts demand and returns, the products buy-back, and the ability to repair the defective spare parts. The decision takers must take into account these factors along with the suppliers reliability and their environmental impact to ensure their client's satisfaction and to lower their environmental impact. This is becoming increasingly important in different decision levels considering that the manufacturing industry is obliged to transform its activities into more environmentally friendly ones (Shi et al., 2015). Spare parts management decision makers must consider the above mentioned variables, their past values and their possible evolution. However, in the industry, this data can be unavailable especially if the spare parts are at the first stages of their life cycles.

The difficulties in collecting this data makes the spare parts management a complex problem for companies (Teixeira et al., 2018). Spare parts classification can be beneficial to construct missing information like reliability, repair ability, and the ability to extract this part from used systems in more advanced phases of its life cycle based on characteristics of the class to which the spare part belongs. Organizations employ spare parts classification to prioritize the most important spare parts classes and to apply the appropriate inventory strategy or forecast for their spare parts. In practice, companies employ ABC classification methods with one criterion which is the annual cost usage of the spare part (Hu et al., 2018). In the literature, multiple criteria classification methods have been investigated for various purposes. The most used criteria for spare parts classification are lead time, number of suppliers, price, annual consumption, stock-out cost, and the probability of failure (Teixeira et al., 2018; Roda et al., 2014; Ghuge et al., 2022). Teixeira et al. (2018) proposes a multi-criteria method to identify the most adapted stock management policy by classifying the spare parts according to their criticality based on their functions and production impact, their lead time, and their price. Ghuge et al. (2022) developed a multi-criteria framework using Delphi, analytical hierarchical process (AHP), and segmentation approaches to determine the most suitable spares to be produced by additive manufacturing according to business impact and technical compatibility criteria. Raja et al. (2016) classified spare parts using hierarchical clustering after defining the clustering variables to develop inventory policies for the different groups of spare parts.In the same vein, Moharana and Sarmah (2018) used hierarchical clustering to find similarities in spare parts to make maintenance work easier. Wang et al. (2006) employed two artificial neural networks (ANNs) to evaluate the criticality of spare parts in a power plant. The authors of the majority of the existing methods define the classification criteria before classifying the spare parts. The unsupervised machine learning methods are less used for spare parts classification. The purpose is usually linked to develop new production and inventory management policies.

In the literature, the spare parts procurement problem have been considered to manage the end of life. It focuses on spare parts with available information since they reach the end of their life cycle. Cattani and Souza (2003) focus on determining the final lot size for regular production. Inderfurth and Mukherjee (2008) and Inderfurth and Kleber (2013) provide an approach to determine optimal spare parts acquisition until EOL. In the same vein, Xu et al. (2014), model the cost to support spare parts acquisition at the end of life of automotive components. In this paper, we build a DSS for spare parts acquisition planning during the entire spare part life cycle considering five options; new parts, parts under warranty, harvested parts from returned products, repaired parts, and a LTB event. The uniqueness of our work is that we provide a decision support model that considers all life cycle phases and that builds the missing information to provide fully informed recommendations of the optimal quantities and period to set these options up and then to cloture them using machine learning models (RFE, SVM, and Hierarchical agglomerative clustering).

2 PROBLEM SETTING

The company needs to take strategic decisions related to the spare parts management all along the part's life cycle. The considered supply options are new parts, parts under warranty (SWAP), repair, spare parts extraction from returned systems (Harvest), and LTB. The decision to introduce a new repair should be done very early in the product/part Life cycle. Ideally at the design of the product/part to limit the required investments. The new repair decision is based on technical assessment and costs evaluation. The harvest process allows to get used spare parts from a functional system after it has been de-installed. Potential harvested parts are validated by Quality tests performed on the system prior to de-installation. Every extracted spare part goes through a quality inspection which allows the organization to assume that the harvest spare parts are as-good-as-new. The set up of a supply option occurs only one time during the part's life cycle. The parts procurement decision should consider demand, consumption, returns, the allowed inventory level, and the capacity of each option. Decisions of spare parts procurement need to be taken all along the part life cycle at the right time. This is a complex process as it should include the mentioned variables in the decision making. The company needs to consider the reverse logistics supply chain options as early as possible in the product life cycle to ensure a better serviceability level, a lower cost, and a lower environmental impact by reducing the use of raw materials.

Assumptions

1. Harvested items, if not sent to repair, are considered as-good-as-new.
2. Parameters prediction is applied using a 2-year Moving Average.
3. Parameters trends depend on the part's life cycle phase.
4. Lead time is assumed to be zero.
5. New buy and LTB have unlimited capacities.
6. Spare parts capture rate from de-installed systems is constant.
7. Probability to de-install systems and IB size are dependent.
8.The company pays all logistic costs.
9.Decision horizon ends at the planned EOL year.

Notations

The model is applied on one spare part and the supply options are $i \in \{1,2,3,4,5\}$ representing consecutively new buy, Swap, Repair, Harvest, and LTB.
S_{it} : Supply chain set-up cost of option i at period t.
P_{it} : Procurement cost of option i at period t.
C_{it} : Closure cost of option i at period t.
IB_t : Installed base of systems containing the part at period t.
L_{it} : Logistics costs of option i at period t.
EF_{it} : Early life failure cost of option i at period t.
β_t : Scrap ratio of parts repair at period t.
θ_t : Early repair ratio of swapped parts at period t.
α_t : Consumption ratio of parts at period t.
γ_t : Swap ratio of parts under warranty at period t.
D_t : Demand at period t.
$Imin_t$: Minimum inventory level at period t.
$Imax_t$: Maximum inventory level at period t.
H_{it} : Inventory holding cost of option i at period t.
S_t : De-installed systems at period t.
Ps_t : Probability to de-install systems at period t.
CR : Capture rate of the spare part from de-installed systems.
K_{it} : Procurement capacity of option i at period t.

Decision variables

X_{it} : Number of parts procured of option i at period t.
y_{it}: binary decision variable representing the existence of option i at period t.
z_{it}: binary decision variable representing the set up of option i at period t.
l_{it}: binary decision variable representing the closure of option i at period t.
I_t: Number of parts in the inventory at period t.

We introduce additional binary variables z_{it},l_{it},b_{1it},c_{1it},b_{2it}, and c_{2it} to linearize the problem. In this closed loop supply chain, dependencies between the five considered supply options must be taken into account. In (Figure 1), we show the spare parts flow in the supply chain and their corresponding parameters.

Mathematical modeling

The goal is to maintain the parts procurement until the products EOL while minimizing the total cost to serve during an observation duration T. A decision to procure parts from a supply option i will be taken on a period t. Therefore, we split the observation duration into T_n periods where $T = \{1,2,..,T_n\}$. The considered costs are the supply chain options set-up and closure costs, the procurement cost, the logistic cost, and the inventory cost. The set-up and closure costs of all supply chain options must be considered as they can impact the total cost to serve and the decision to procure or not the parts. These costs must occur only once in a spare part life cycle. They are computed in Equations (1) and (2).

$$C_1 = \sum_{t=1}^{T_n} \sum_{i=1}^{5} max(y_{it} - y_{it-1}, 0) \cdot S_{it}, \qquad (1)$$

$$C_2 = \sum_{t=1}^{T_n} \sum_{i=1}^{5} max(y_{it-1} - y_{it}, 0) \cdot C_{it}. \qquad (2)$$

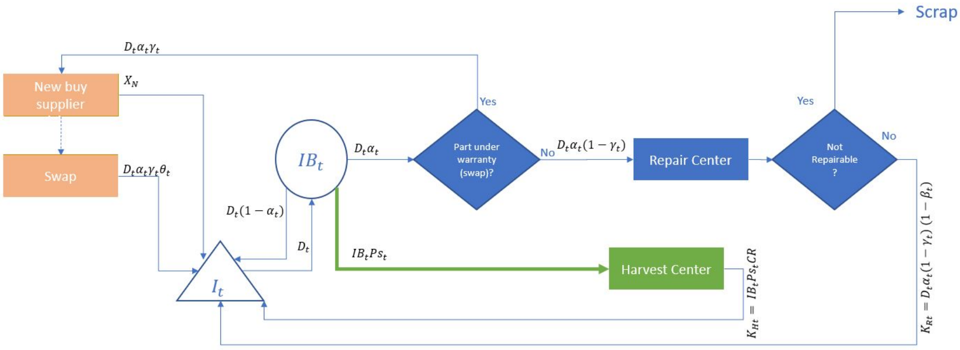

Figure 1: The closed loop supply chain options of spare parts.

The most impacting cost is the procurement cost which can be high if the quality of the part is poor and more spare parts must be bought. For this reason, we consider an early failure rate that describes the spare part failure probability at the beginning of its life to add a quality cost. This is shown in Equation (3).

$$C_3 = \sum_{t=1}^{T_n}\sum_{i=1}^{5} X_{it} \cdot P_{it} \cdot (1+EF_{it}). \tag{3}$$

The transport cost is considered the same for all supply options. However, in total, the logistic cost depends on the item quality and therefore on the early life failure as the part will be taken back to the warehouse and then another part should be taken to the client to replace it. This is described by Equation (4).

$$C_4 = \sum_{t=1}^{T_n}\sum_{i=1}^{5} X_{it} \cdot l_{it} \cdot (1+2EF_{it}). \tag{4}$$

As it is detailed in Equation (5), an inventory holding cost is considered to jointly optimize the spare part procurement process and the inventory level at each period.

$$C_5 = \sum_{t=1}^{T_n}\sum_{i=1}^{5} X_{it} \cdot H_{it}. \tag{5}$$

We denote the total cost by TC. We have

$$\begin{aligned} TC &= C_1 + C_2 + C_3 + C_4 + C_5 \\ &= \sum_{t=1}^{T_n}\sum_{i=1}^{5} max(y_{it} - y_{it-1}, 0) \cdot S_{it} \\ &+ max(y_{it-1} - y_{it}, 0) \cdot C_{it} \\ &+ X_{it} \cdot P_{it} \cdot (1+EF_{it}) \\ &+ X_{it} \cdot l_{it} \cdot (1+2EF_{it}) + X_{it} \cdot H_{it}. \end{aligned} \tag{6}$$

To linearize the problem, we use decision variables $Z_{it}, l_{it} \in \{0,1\}$.

$$\begin{aligned} TC = \sum_{t=1}^{T_n}\sum_{i=1}^{5} & z_{it} \cdot S_{it} + l_{it} \cdot C_{it} \\ & + X_{it} \cdot (P_{it} + l_{it} + EF_{it}(P_{it} + 2l_{it}) + H_{it}). \end{aligned} \tag{7}$$

The mathematical model is given by

$$\min\ TC. \tag{8}$$

Subject to
$\forall t \in \{1,..,T_n\}$ and M is a big number,

$$X_{it} \in \mathbf{N}, y_{it}, z_{it}, l_{it}, b_{1it}, c_{1it}, b_{2it}, c_{2it} \in \{0,1\}, \tag{9}$$

$$X_{it} < My_{it},\ \text{for } i \in \{1,..,5\}, \tag{10}$$

$$z_{it} >= y_{it} - y_{it-1},\ \text{for } i \in \{1,..,5\}, \tag{11}$$

$$z_{it} <= y_{it} - y_{it-1} + (1-b_{1it}) \cdot M,\ \text{for } i \in \{1,..,5\}, \tag{12}$$

$$z_{it} <= (1-b_{2it}) \cdot M,\ \text{for } i \in \{1,..,5\}, \tag{13}$$

$$b_{1it} + b_{2it} = 1,\ \text{for } i \in \{1,..,5\}, \tag{14}$$

$$l_{it} >= y_{it-1} - y_{it},\ \text{for } i \in \{1,..,5\}, \tag{15}$$

$$l_{it} <= y_{it-1} - y_{it} + (1-c_{1it}) \cdot M,\ \text{for } i \in \{1,..,5\}, \tag{16}$$

$$l_{it} <= (1-c_{2it}) \cdot M,\ \text{for } i \in \{1,..,5\}, \tag{17}$$

$$c_{1it} + c_{2it} = 1,\ \text{for } i \in \{1,..,5\}, \tag{18}$$

$$\sum_{t=1}^{T_n} z_{it} \leq 1,\ \text{for } i \in \{1,..,5\}, \tag{19}$$

$$\sum_{t=1}^{T_n} l_{it} \leq 1,\ \text{for } i \in \{1,..,5\}, \tag{20}$$

$$X_{it} \leq K_{it},\ \text{for } i \in \{2,..,4\}, \tag{21}$$

$$I_t = I_{t-1} + \sum_{i=1}^{5} X_{it} - D_t, \tag{22}$$

$$I_t \geq Imin_t, \tag{23}$$

$$I_t \leq Imax_t. \tag{24}$$

The decision variables and the additional constraints for the model lnearization are defined in constraint (9). Constraint (10) states that a quantity of procured spare parts can be obtained only if the supply option exists which means that a decision to set it up has been made in a previous or in the same period. Constraints ((11)-(18)) describe the added decision variables z_{it} and l_{it} to linearize the problem. A supply option cannot be set up and closed more than one time in the part's life cycle. This is integrated in the model in constraints (19) and (20). Constraint (21) represents the capacity constraint of each supply option with limited capacity in a period t. The parts procurement process must satisfy the inventory constraints ((22)-(24)).

In an industrial context, data is not always available especially if the concerned spare part is at the beginning of its life cycle. Therefore, we build a DSS that imputes the lacking data, predicts the future values using a 2-year moving average and a linear evolution function with a slope that changes according to the life cycle phase and then provides recommendations using a Mixed Integer Linear Programming (MILP) model. As it is shown in (Figure 2), in case of lacking information, we start by selecting the most impacting features on the availability of spare parts from each supply chain option using the recursive feature elimination (RFE) model. Once the features are selected, we identify the parts classes using Hierarchical Agglomerative clustering. Finally, we predict the class of a given spare part using Support Vector Machine (SVM).

3 USE CASE

A numerical study is applied on a spare part from General Electric Healthcare that has 8 years to reach the end of its life. The SWAP option is not available for this spare part. Repair and Harvest procurement costs are lower than the new buy cost. We assume that the values of demand, Consumption, returns, and Installed Base (IB) size are decreasing since the need for this spare part will continue to decrease and there will be no more de-installations until the EOL. This is shown in (Figure 3) and (Figure 4). For the probability of the linked systems de-install, we consider that it will continue to increase until the EOL.** We consider that all de-installed systems return to the company. Therefore, we apply an increasing slope to the two years moving average prediction of the systems de-installations for all systems in which we can find the spare part. All the parameters are known except for the Harvest capture rate as it has not been harvested before. To impute the missing data, we apply the clustering approach and we complete the harvest information using the average value of the class to which the spare part belongs.These information can also be based on the systems average capture rates of other different spare parts. However, a capture rate depends not only on the product from which the part is extracted, but especially on the spare part's characteristics like the extraction lead times, the part type, and quality.

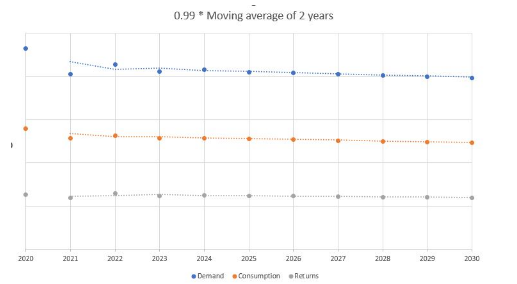

Figure 3: Demand, consumption, and return trends in decision horizon.

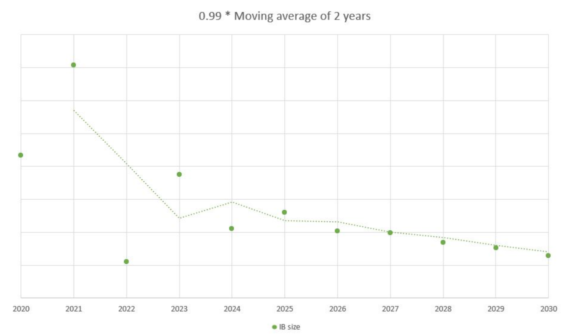

Figure 4: IB size trend in decision horizon.

The clustering method will allow us to provide more accurate information. We start by selecting the most impacting features using RFE. The chosen features are annual demand, warranty, repair ability, age, part criticality, annual forecast, quality, part/product type, product market segment, priority score, and life cycle phase. The RFE model score is evaluated by predicting the spare parts supply options availability using an SVM model with only the selected features and it shows a score of 98%. Then, using these features, we apply Hierarchical agglomerative clustering. We choose the optimal number of clusters based on hierarchical structure of the dendrogram. The spare parts can be divided into two classes as it is shown in the dendrogram in (Figure 8).

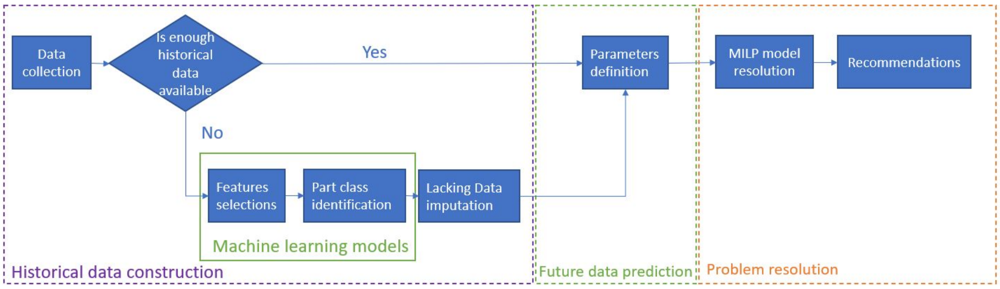

Figure 2: The DSS process.

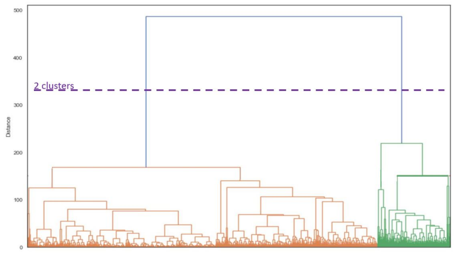

Figure 5: Clusters dendrogram.

Then, we label our data and use SVM model to predict to which class our spare part belongs. An average Harvest capture rate from the spare part's class is calculated and employed to forecast the Harvest capacity for the next periods until EOL using the BKB model introduced in Turki et al. (2022).

To provide recommendations based on the optimal solution, we start with an inventory that contains the allowed maximum quantity. Different cases are evaluated to test the model's recommendations according to the capacities of each supply chain option. The recommendations of the different cases are illustrated in (Figures 6-9).

Case 1: The only available option is new buy with unlimited capacity and there is no LTB event. The system recommends to buy new spare parts each period to meet the demand and respect the inventory constraints. At the end of the last period there must be no quantities left in the inventory since the spare part reaches its EOL.

Case 2: New buy is available with unlimited capacity, repair and Harvest are available with limited capacities. The system recommends starting spare parts procurement of repair and harvest from the first period and buying more spare parts in the second period and less quantities in the first period since the stock holding cost is higher than the procurement cost of repair and harvest items. This case total cost is lower by 9.7% than the first case total cost.

Case 3: New buy is available until the 6th period, then a LTB event is available at the 7th period and no other supply option is available. The system recommends no changes at the five first periods compared to case 2. At the 6th period, and before having to pay for a LTB, it recommends buying spare parts that exceed the demand to stock them for the next year and limit the cost of the LTB procurement. The system recommends buying the sum of the needed quantities until the EOL at the 7th period and provides a planning of what can be used by looking at the demand of each period.

Case 4: New buy is available until the 6th period, then a LTB event is available at the 7th period. Repair and harvest supply options are available with limited capacity until EOL. With the existence of other options, the model recommends buying the maximum capacity from repair and harvest and procuring the rest from the LTB. The LTB quantity procured in the 7th period is also divided into two periods to minimize the total cost of spare parts procurement from these different options. This option's total cost is lower than the case 3 total cost by 9.2%.

4 CONCLUSION & PERSPECTIVES

In this paper, we provided a DSS for spare parts procurement planning all along the part life cycle. We take into account that, in an industrial context, the needed information to resolve this problem is not always available. Taking a decision to manage spare parts needs to consider different factors that can impact both the inventory and the clients satisfaction. To resolve this problem, we provided a process that classifies the spare parts according to the most impacting features on the different supply options availability chosen by an RFE model. We provided a use case for a spare part from

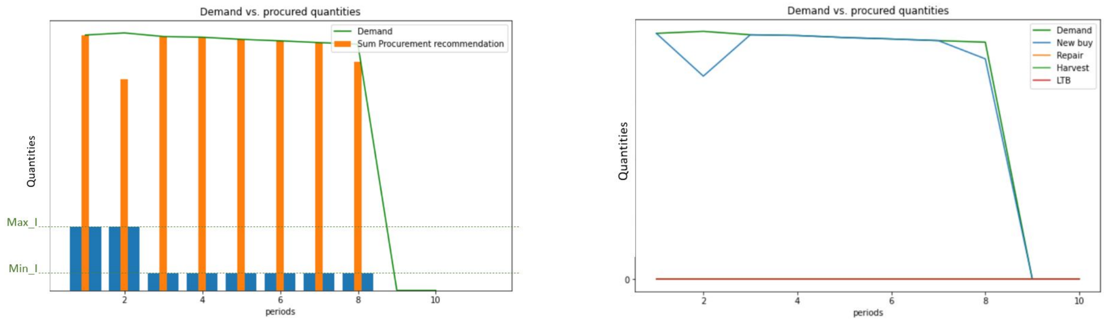

Figure 6: Case 1 results.

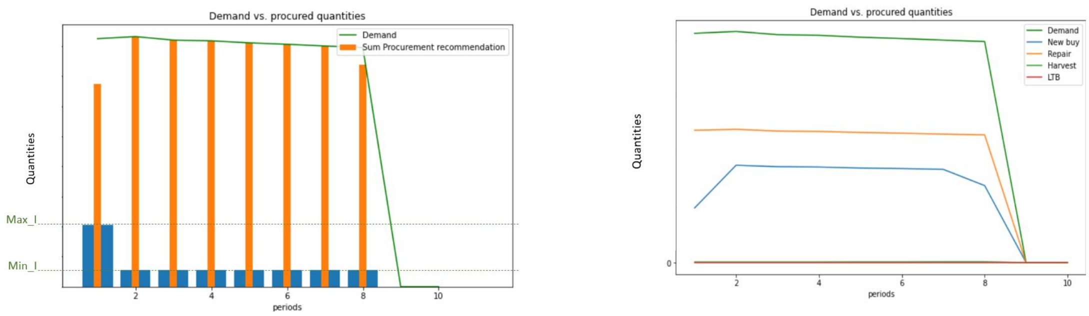

Figure 7: Case 2 results.

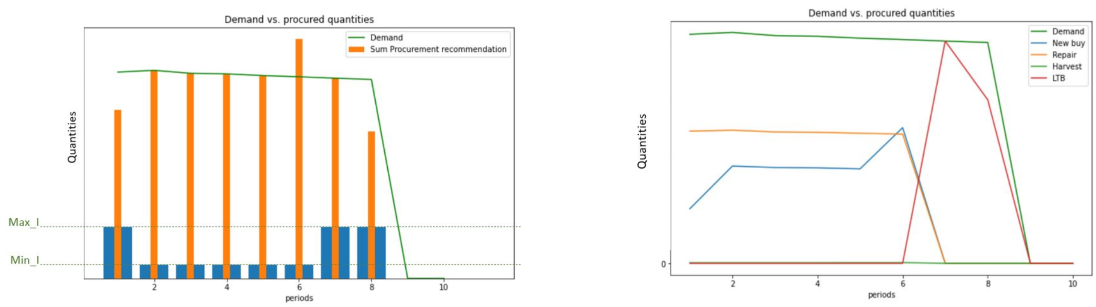

Figure 8: Case 3 results.

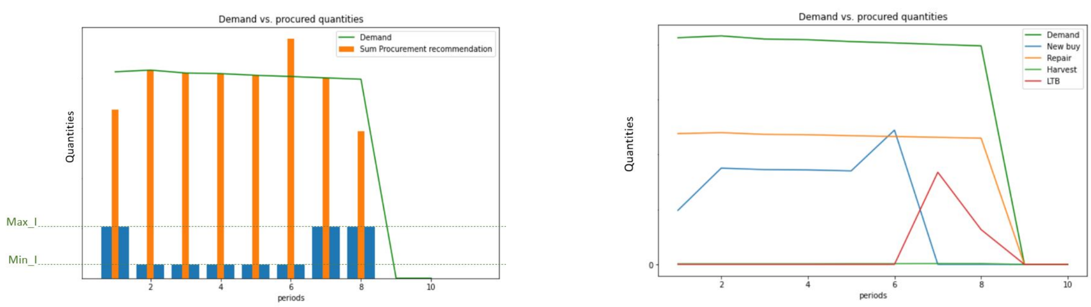

Figure 9: Case 4 results.

General Electric Healthcare. We identified the item's class using an SVM model, and imputed the missing information using an average of the harvest capture rate for spare parts from its class. The recommendations of the proposed approach show that, if we have all of the needed information and if the supply options of repair and harvest exist the system will recommend buying from them as soon as possible. We can decrease the total cost of the spare parts procurement by at least 9%. This approach should be tested on a spare part at the beginning of its life cycle. Future research can consider the environmental impact of the supply options in the decision making. Another improvement axis is developing a more advanced method for data imputation.

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